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Chen, T.; van der Werf, G.R.; Dolman, A.J.; Groenendijk, M.

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Evaluation of cropland maximum light use efficiency using eddy flux measurements in North America and Europe

Tiexi Chen,[1,2] Guido R. van der Werf,[1] A. J. Dolman,[1] and M. Groenendijk[1]

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[1] Croplands cover 12% of the ice-free land surface and play an important role in the global carbon cycle. Light use efficiency (LUE) models have often been employed to estimate the exchange of CO_2 between croplands and the atmosphere. A key parameter in these models is the maximum light use efficiency (ε*), but estimates of ε* vary by at least a factor 2. Here we used 12 agricultural eddy-flux measurement sites in North America and Europe to constrain LUE models in general and ε* in particular. We found that LUE models could explain on average about 70% of the variability in net ecosystem exchange (NEE) when we increased the ε* from 0.5 to 0.65–2.0g C per MJ Photosynthetic Active Radiation (PAR). Our results imply that croplands are more important in the global carbon budget than often thought. In addition, inverse modeling approaches that utilize LUE model outputs as a-priori input may have to be revisited in areas where croplands are an important contributor to regional carbon fluxes. **Citation:** Chen, T., G. R. van der Werf, A. J. Dolman, and M. Groenendijk (2011), Evaluation of cropland maximum light use efficiency using eddy flux measurements in North America and Europe, *Geophys. Res. Lett.*, *38*, L14707, doi:10.1029/2011GL047533.

1. Introduction

[2] Globally, crop ecosystems cover about 12% of the ice-free land surface. Regionally, this fraction can increase to 33% in Europe and 20% in the United States [*Ramankutty et al.*, 2008]. *Schulze et al.* [2009] suggested that croplands are a net source of greenhouse gasses to the atmosphere in Europe. In contrast, croplands were identified as a sink in the United States [*West et al.*, 2010]. *Smith et al.* [2008] proposed that croplands could have a large potential in greenhouse gas mitigation through specific GHG-management practices, and different local management practices may be one of the reasons why croplands sometimes appear as a source and sometimes as a sink in different regions of the world.

[3] Designed as a core infrastructure of the global terrestrial monitoring network [*Running et al.*, 1999], the eddy covariance technique is a widely used method to observe carbon fluxes between the land surface and the atmosphere [*Baldocchi et al.*, 2001]. The data is particularly useful to study terrestrial ecosystem carbon cycle processes on time scales from hourly to yearly. Eddy covariance flux tower (ECFT) measurements are widely used across a variety of terrestrial ecosystems, including croplands. ECFT measure the net flux of carbon dioxide (net ecosystem exchange [NEE]), which can be separated into an assimilation component (gross primary production [GPP]), and the respiration component (total ecosystem respiration [RE]) using techniques developed for instance by *Reichstein et al.* [2005]. In addition to flux measurements, additional observations are usually made including photosynthetic available radiation (PAR). This data stream offers an opportunity to study the light use efficiency of croplands.

[4] Light use efficiency (LUE) models are widely used to diagnose terrestrial ecosystem productivity such as gross primary productivity (GPP) and net primary productivity (NPP, GPP minus autotrophic respiration) [*Field et al.*, 1998; *Running et al.*, 2004]. NPP and GPP can be expressed as a product of intercepted photosynthetically active radiation (IPAR) and a light use efficiency coefficient; ε [*Monteith*, 1972, 1977]. While the LUE approach has become widely accepted, the exact determination of the core parameter ε*, the potential maximum ε that may be reached when temperature and moisture are not limiting plant carbon uptake, is still problematical. *Zhang et al.* [2008] suggested to increase the cropland ε* in the algorithm used to derive GPP and NPP from the Moderate Resolution Imaging Spectroradiometer (MODIS) MOD17 product after calibration with flux data from a site with double-cropped winter wheat and summer maize in China. Besides the MOD17 product, remote sensing data from the MODIS instruments include the fraction of photosynthetically active radiation (fPAR) at 1 km^2 [*Running et al.*, 1999]. We evaluated ε* of croplands using flux tower measurements and MODIS derived fPAR data together with the Carnegie-Ames-Stanford Approach (CASA) biogeochemical model across North America and Europe to determine whether the default value of ε* is representative and if not, what it should be to capture the carbon dynamics observed by ECFT over croplands.

2. Methods

2.1. Site Description

[5] There are around thirty cropland sites in the FLUXNET database (www.fluxdata.org). Twelve of these sites had at least 2 years of data and contained also meteorological parameters such as PAR, temperature, and precipitation. We chose these twelve sites for our analysis, evenly spread over North America and Europe (auxiliary material, Table S1).[1]

[1]Faculty of Earth and Life Sciences, VU University Amsterdam, Amsterdam, Netherlands.
[2]School of Atmospheric Sciences, Nanjing University, Nanjing, China.

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[1]Auxiliary materials are available in the HTML. doi:10.1029/2011GL047533.

Table 1. Statistical Information Between ECFT Observation and Modeling Results[a]

	NPP($\varepsilon^*_{0.5}$), GPP(ECFT)				NEE(ε^*_{opt}), NEE(ECFT)		
Site Code	Correlation, r	Variance Rate	Plant Type	Optimized ε^*	Correlation, r	Variance Rate	ε (L)
BE-Lon	0.76	0.03		1.55	0.64	0.39	1.96
DE-Geb	0.7	0.06		0.9	0.57	0.32	1.86
DE-Kli	0.95	0.05		1.25	0.83	0.71	1.61
DK-Ris	0.91	0.01		2	0.9	0.29	2.91
ES-ES2	0.95	0.04	rice	1.15	0.86	0.74	1.55
FR-Gri	0.58	0.05		0.9	0.54	0.3	1.92
US-ARM	0.92	0.2	wheat	0.85	0.85	0.76	0.37
US-Bo1	0.9	0.05			0.84	0.69	
US-Bo1a	0.88	0.06	soybean	0.85	0.83	0.67	2.16
US-Bo1b	0.94	0.05	corn	1.3	0.86	0.74	1.87
US-IB1	0.89	0.05			0.93	0.81	
US-IB1a	0.94	0.04	corn	1.45	0.98	0.94	1.96
US-IB1b	0.83	0.07	soybean	0.9	0.86	0.7	1.31
US-Ne1	0.95	0.03	corn	1.7	0.93	0.84	2.26
US-Ne2	0.89	0.03			0.93	0.88	
US-Ne2a	0.96	0.02	corn	1.9	0.95	0.93	2.22
US-Ne2b	0.87	0.07	soybean	0.65	0.77	0.57	1.66
US-Ne3	0.85	0.04			0.91	0.81	
US-Ne3a	0.92	0.02	corn	1.95	0.93	0.87	1.99
US-Ne3b	0.87	0.07	soybean	0.7	0.76	0.6	1.39

[a]Correlation and variance rate between NPP(CASA with default $\varepsilon^* = 0\ 5$ gCMJ^{-1}) and GPP(ECFT measurement), and between NEE(CASA with optimized ε^*) and NEE from ECFT measurement. ε (L) see section 3.4.

2.2. Photosynthetically Active Radiation From MODIS Land Products Subsets

[6] MODIS land products subsets are provided at 1km resolution for a 7*7 km box centered on the flux towers through the Oak Ridge National Laboratory Distributed Active Archive Center [*Distributed Active Archive Center*, 2010]. These subsets are specifically designed for validation of models and remote sensing products, or for characterization of field sites (http://daac.ornl.gov/cgi-bin/MODIS/GR_col5_1/mod_viz.html). Following previous studies [*Connolly et al.*, 2009; *Zhang et al.*, 2007], we only used data from the center pixel where the tower was located.

2.3. Model and Optimized Method

[7] The CASA biogeochemical model that is used here [*Potter et al.*, 1993] is based on the LUE approach and operates with a monthly time step. The general equation of LUE models is:

$$NPP = PAR \times fPAR \times f(\varepsilon) \times \varepsilon^*$$

where f(ε) accounts for the effects of environment stress including water stress and temperature effects. Empirical studies suggested that ε^* for NPP calculations (here denoted as ε^*(NPP)) varies between 1.1 and 1.4 g C MJ^{-1} for croplands [*Russell et al.*, 1989]. In the CASA version used here [*van der Werf et al.*, 2010], ε^*(NPP) was set to 0.5 g C MJ^{-1} globally to match global NPP values of 60 Pg C year^{-1} [*Beer et al.*, 2010]. The Q10 value which governs the temperature response of heterotrophic respiration was set to 1.5 in the soil sub-model and CASA was spun up with the average input data for 250 years, when assimilation was equal to respiration on an annual scale. We ran CASA with meteorological data (PAR, temperature, precipitation) measured by the ECFT. We first ran CASA with the default ε^*(NPP) (0.5 g C MJ^{-1}), and then increased ε^*(NPP) with steps of 0.05, keeping the other input datasets - which are better constrained than ε^* - constant. The ε^*(NPP) value corresponding to the lowest root mean square difference between FLUXNET observed NEE and simulated NEE from CASA was then considered optimal:

$$RMSE = \left[\frac{1}{N}\sum_{n=1}^{N}(NEE_{CASA} - NEE_{ECFT})^2\right]^{1/2}$$

3. Results

3.1. NPP Comparisons

[8] Most LUE-based models use the same equation to estimate GPP and NPP, the difference often lies in a different ε^*. Therefore the ratio between GPP and NPP is constant in most LUE approaches, allowing us to compare the variability in CASA-derived NPP with ECFT-derived GPP. Correlation coefficients between NPP and GPP varied between 0.58 and 0.96 with an average of 0.87 (Table 1).

3.2. NEE Comparisons

[9] Modeling NEE with the default ε^*(NPP) of 0.5 g C MJ^{-1}, and with optimized ε^*(NPP) were both compared with ECFT measured NEE. We used Taylor diagrams [*Taylor*, 2001] to quantitatively depict the comparison. Since the measurement values vary between sites, the data was normalized first to plot all sites in one single diagram.

[10] Figure 1 shows the Taylor diagrams [*Taylor*, 2001], and a time series for one site is given as an example in Figure 2. For the Taylor diagrams, we divided the model results and ECFT measurements by the standard deviation of the corresponding ECFT measurements. Therefore, there is only one reference point indicating the measured NEE which is located on the x-axis at unity. Thus, ECFT

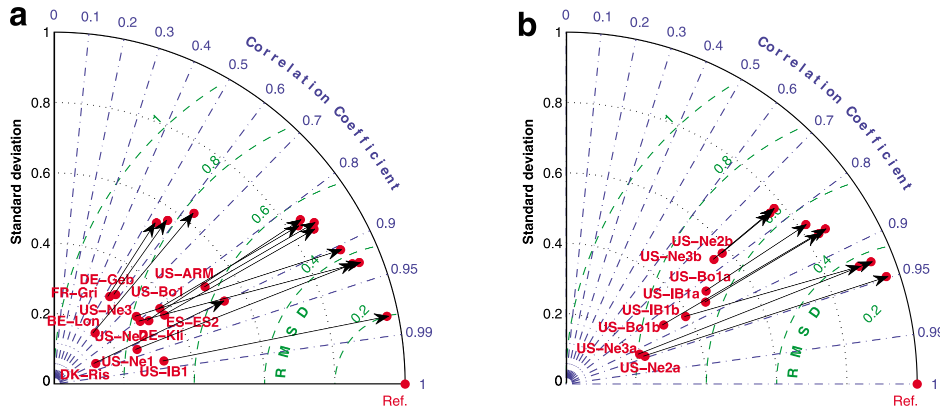

Figure 1. CASA modeled NEE compared with ECFT measurements in normalized pattern statistics. Site codes are described in Table 1. Original modeling results with ε*(NPP) = 0.5 gCMJ^{-1} for NEE are plotted at the tail of the arrows, and the rows point refer to revised modeled NEE with optimized ε*(NPP). Ref point indicates the NEE measured at the ECFT. (a) The 12 sites used in this study and (b) only those sites with plant rotation information (plant type information in Table 1).

measurements have the same standard deviation (normalized to 1) in the Taylor diagram. We found that correlation coefficients between predicted and observed fluxes varied between 0.54 and 0.98. These values were identical for original and optimized ε*(NPP) because a change in ε*(NPP) operates linearly. Original modeled NEE with default ε*(NPP) compared poorly with ECFT observations, showing a uniform underestimation of the standard deviation which only explained between 2% and 34% of the ECFT NEE variance, with an average of 13%. A significant improvement in the amplitude of NEE variations was made with our optimized ε*(NPP) where NEE from CASA explained ECFT NEE variance of about 29% to 94%, with an average value of 68%.

3.3. Values of ε*(NPP)

[11] Our optimized ε* values for the 12 cropland sites varied between 0.65 and 2.0 g C MJ^{-1} (Table 1). Importantly, ε* changed with crop type; the lowest values were found for wheat (0.85 g C MJ^{-1} at one site) and soybean (0.65–0.90 g C MJ^{-1} at 4 sites), while rice (1.15 g C MJ^{-1} at one sites) and corn (1.30–1.95 g C MJ^{-1} at 5 sites) had higher values. These values fall within the range compiled by *Lobell et al.* [2002].

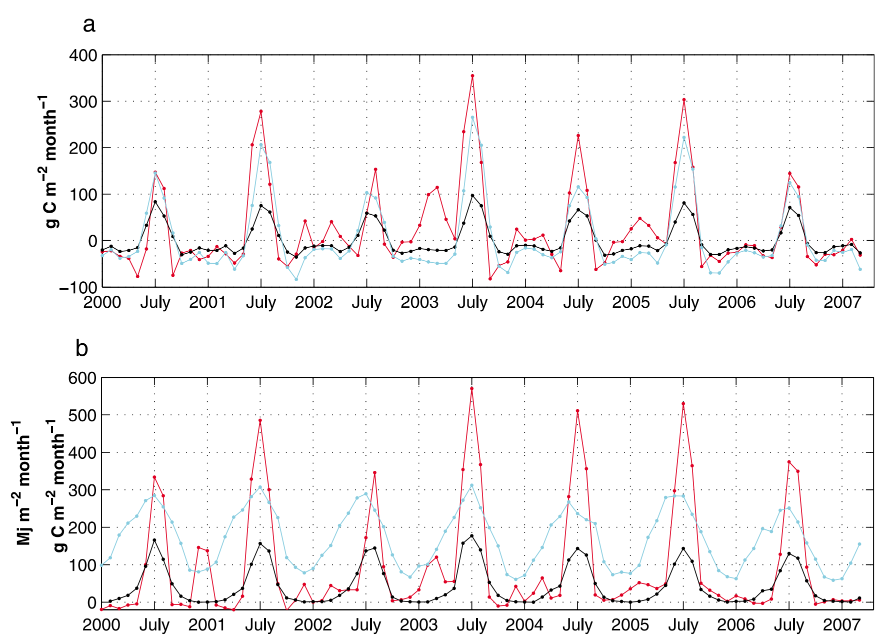

Figure 2. Example time series of monthly carbon flux information, site BO Bondville, IL USA. (a) CASA modeled NEE with default ε of 0.5 g C MJ^{-1} (black), with optimized ε*(cyan), and ECFT NEE (red). (b) GPP as measured by ECFT (red), and from MOD17 (black). Cyan line indicates photosynthetically active radiation (PAR in MJ m^{-2} month^{-1}).

3.4. Values of ε*(GPP) MOD17 GPP Comparison With ECFT

[12] The MODIS GPP product MOD17 is also based on the LUE approach, with an ε*(GPP) of 0.68 g C MJ^{-1} for croplands [*Heinsch et al.*, 2003]. Here we simply calculated observed light use efficiency ε(GPP) as the ratio between measured GPP and incident photosynthetically active radiation (PAR) at ECFTs, i.e. ε(GPP) = fPAR × f (ε) × ε* (GPP). This approach neglects potential limitations that could lower ε from its maximum value, but this effect is likely minimal in well-watered crops in the growing season when fPAR is close to unity. Crops have in general a more pronounced growth cycle than natural ecosystems due to set planting and harvesting dates. We defined the growing season from May to August based the observed seasonality in the ECFTs. We then chose the largest ε(GPP) over these 4 months, denoted as ε(L). We found that ε(L) ranged between 1.31 and 2.91 g C MJ^{-1}, with one outlier; an ε(L) of 0.37 g C MJ^{-1} (Table 1).

4. Discussion and Conclusions

[13] The LUE approach is commonly used to estimate the efficiency of radiation conversion to plant production, both for GPP [*Zhao and Running*, 2010] and for NPP [*Field et al.*, 1995]. By including respiration and other carbon loss processes, a biogeochemical model such as CASA could further calculate NEE, representing the net carbon flux between ecosystems and the atmosphere. NEE is also measured directly using the eddy-covariance method, allowing for a direct model – measurement comparison. When using the 'standard' ε*(NPP) value of 0.5 g C MJ^{-1}, CASA captured 2%–34% (range) of the temporal variability in NEE in the 12 cropland sites we investigated.

[14] To capture the NEE magnitude, the model required a substantial increase in ε*(NPP) for all 12 cropland sites. On average, we found that an ε*(NPP) of 1.25 g C MJ^{-1} yielded the lowest RMSE when assessing the performance of all sites, with individual sites ranging from 0.65 to 2.0 g C MJ^{-1}. Although most models use a constant ε*(NPP) value for different crop types, our findings indicate that different crop types may have different ε*(NPP) values, although a larger number of sites for each individual crop type is required to gain more confidence in the exact values. For example, while we included both irrigated and non-irrigated sites in our study, we could not systematically assess the impact of irrigation on ε* due to the limited number of station. Our finding of an underestimation of ε* also applied to the MODIS MOD17 GPP product over crop sites.

[15] Our results are somewhat sensitive to the parameterization of respiration in CASA, because lower respiration fluxes could in principle explain part of the mismatch we found between modeled and measured NEE. Figure S1 shows that this is unlikely to explain a substantial part of the mismatch because with lower respiration fluxes (autotrophic and / or heterotrophic) and consequently lower NPP values the NPP during the growing season would be lower than NEE, which is physically not plausible. *Moors et al.* [2010] suggested the ratio of NPP to NEE to be about 1.6 for croplands during the growing season. With optimized ε*, our results indicated a ratio of 1.7 on average (Figure S1). In addition, the sensitivity of our results to changes in heterotrophic respiration is modest; by changing the Q_{10} value to a range between 1 and 2 (Table S2) we found that the average optimized ε* ranged between 0.98 and 1.43, instead of the value of 1.25 we derived with the standard Q_{10} value of 1.5.

[16] Besides the limited number of cropland sites available, uncertainties exist due to the scaling of the 1 km^2 pixel located on the flux tower which may not be fully representative of the flux tower footprint. Tower measurements in general represent a horizontal range of about 500 m around the tower [*Running et al.*, 1999], although the actual fetch will vary with wind (speed and direction) and surface roughness and other meteorological conditions [*Schmid*, 2002].

[17] In addition to the MODIS data, we also used the JRC-fPAR product [*Gobron et al.*, 2010]. The comparison showed a reasonable level of agreement between the two products with no overall bias (Figure S2). Using the JRC-fPAR product would therefore not change our main conclusions. We did not include site-specific details on management regimes and stage in the crop rotation cycle, which may impact carbon fluxes. By including as many sites as possible (n = 12) some of these factors will average out, but care should be taken with interpreting the results for individual sites.

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T. Chen, A. J. Dolman, M. Groenendijk, and G. R. van der Werf, Faculty of Earth and Life Sciences, VU University Amsterdam, De Boelelaan 1085, Amsterdam, NL-1081 HV, Netherlands. (tchen@falw.vu.nl; han.dolman@geo.falw.vu.nl; margriet.groenendijk@falw.vu.nl; guido.van.der.werf@falw.vu.nl)